FINAL REPORT
IRO REPORT NO. 212A



# OVERHAUL FACTOR FORECASTING



MAY 1975

INSTITUTE OF LOGISTICS RESEARCH
US ARMY
LOGISTICS MANAGEMENT CENTER
FORT LEE VIRGINIA
23801

USAMC Inventory
Research Office
Frankford Arsenal





Approved for Public Release; Distribution Unlimited

56

[illegible]

FINAL REPORT

BY

[illegible]

[illegible]



AMC Inventory Research Office
US Army Logistics Management Center
Fort Lee, Virginia

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

# REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER: IRO Report No. [illegible]12A
2. GOVT ACCESSION NO.:
3. RECIPIENT'S CATALOG NUMBER:
4. TITLE (and Subtitle): Overhaul Factor Forecasting
5. TYPE OF REPORT & PERIOD COVERED: Final Report
6. PERFORMING ORG. REPORT NUMBER:
7. AUTHOR(s): Peter R. Fatianow
8. CONTRACT OR GRANT NUMBER(s):
9. PERFORMING ORGANIZATION NAME AND ADDRESS: AMC Inventory Research Office, US Army Logistics Management Center
10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS:
11. CONTROLLING OFFICE NAME AND ADDRESS: HQ, US Army Materiel Command, Maintenance Directorate, AMCMA, 5001 Eisenhower Ave., Alexandria, VA 22333
12. REPORT DATE: April 1975
13. NUMBER OF PAGES: 53
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office):
15. SECURITY CLASS. (of this report): UNCLASSIFIED
15a. DECLASSIFICATION DOWNGRADING SCHEDULE:
16. DISTRIBUTION STATEMENT (of this Report): Approved for Public Release; Distribution Unlimited
17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report):
18. SUPPLEMENTARY NOTES: Information and data contained in this document are based on input available at the time of preparation. Because the results may be subject to change, this document should not be construed to represent the official position of the U.S. Army Materiel Command unless so stated.
19. KEY WORDS (Continue on reverse side if necessary and identify by block number):
Forecasting
Overhaul
Maintenance
Exponential Smoothing
Repair parts

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Results from a study of techniques for forecasting overhaul factors are reported. Techniques evaluated include cumulative history, moving average, and single and adaptive exponential smoothing. A modified version of the exponential smoothing technique produced the best results. The study was based on data reported over a five year period on overhaul programs on 53 reparable items involving 8614 repair parts.

DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

## SUMMARY

The report presents results from a study of forecasting repair part consumption in depot overhaul programs for reparable items. Consumption data reported over a five year period on overhaul programs for 53 reparable items involving 8614 parts were used to simulate overhaul factor forecasting under a number of different forecasting techniques. Comparative evaluations of the moving average, simple exponential smoothing, adaptive smoothing techniques and techniques used in the materiel management system of the US Army Materiel Command are presented. Actual consumption of parts varies considerably from program to program. This variability obscures the significance of differences in forecast accuracy achieved by the forecasting techniques investigated. A modified exponential smoothing technique (MODEXPO) developed in the course of the study was found to be superior to the other techniques evaluated.

MODEXPO is based on the single exponential smoothing technique modified to take advantage of routinely recorded empirical data on Army depot maintenance overhaul programs in forecasting the "depot overhaul factor" (DOF). The DOF is defined as the quantity of a repair part consumed per reparable item overhauled. Due to data recording and reporting procedures, actual values of the DOF can only be estimated from the total quantity of a repair part (Q) consumed in overhauling a certain quantity (N) of a given reparable item. An estimate of the DOF is the ratio Q/N.

In single exponential smoothing, the smoothing constant is usually not explicitly related to information on the process affecting the actual observations. Under MODEXPO, the smoothing constant is based on N and on the "average yearly maintenance program quantity" (P) where $P \geq N$. It is derived so that, for example, consumption observed in overhauling 100 reparable items is given more weight in forecasting the DOF for the next program than if consumption had been observed on only 5 reparable items.

It is recommended to replace the DOF forecasting technique in use at AMC depots with the MODEXPO technique with a 1-year average maintenance program quantity as parameter. Also, Command level overhaul factors should be estimated from the DOFs by a formula defined to form a weighted average based on the average yearly maintenance program for each depot.

# PREFACE

Several members of the [illegible] staff worked on the study reported herein. Mr. [illegible] Kaplan contributed significantly in all areas of this work and especially in the development of the modified exponential smoothing technique. Messrs. [illegible] and [illegible] provided [illegible] assistance in programming, the simulation and the generation of the data bases.

The excellent cooperation of Mr. Charles [illegible] of the US Army Electronics Command and Messrs. [illegible], W. Robinson and [illegible] of the US Army Troop Support Command in furnishing demand data is acknowledged.

The contributions through advice and counsel of [illegible] of the US Army Materiel Command and Messrs. [illegible] Bell and A. [illegible] of the US Army Materiel Systems Analysis Activity are also recognized.

TABLE OF CONTENTS

# CHAPTER I

## INTRODUCTION

### 1.1 Project Background

Differences between forecasted and actual consumption of repair parts for overhaul of reparable end items or assemblies at the Army depot level of maintenance are, in general, quite large. At the time of initiation of this project, forecasts made for procurement and stock control purposes at National Inventory Control Points (NICPs) of Commodity Commands of the US Army Materiel Command (AMC) were based on a different forecasting technique than that used at the overhaul performing depots to forecast their individual requirements. It was not clear which of these two different techniques produced better forecasts, or whether other forecasting techniques would or would not be superior to those being used. In addition, the basic input data was processed twice, first at the depot and then again at the Command level.

The quantitative forecast of repair part requirements is a function of the number of unserviceable items planned for overhaul. This number is forecasted prior to actual availability of these assets at the depot overhaul facility. Thus, the accuracy of the forecast of reparable asset returns also affects the quality of requirements estimates. Recognition of these problems by the Maintenance Directorate at AMC Headquarters initiated the USAMC Inventory Research Office (IRO) study effort on depot maintenance forecasting and scheduling.

### 1.2 Scope of Report

This report covers the investigation of different techniques which could be employed in forecasting the "overhaul factor" parameter needed to estimate repair part requirements. Study results on unserviceable asset return forecasting are reported in Reference 1.

### 1.3 Organization of Report

Chapter II presents a summarized description of the research problem environment, concepts and structure and the approach taken to arrive at

a solution. Chapter III provides descriptions of the data base and of the forecasting techniques considered. Evaluation criteria and rationale applied to enable a choice among alternatives are discussed in Chapter IV. The error statistics used for evaluation and a brief description of the computerized logic developed for simulating forecasting under the various techniques are presented. Chapter V covers results obtained from inquiries with military and non-military organizations on depot type overhaul and results from computer simulation runs. Conclusions and recommendations are then stated. Supplemental information and mathematical details are included in the Appendix.

## CHAPTER II

## DESCRIPTION OF RESEARCH PROBLEM

### 2.1 Overhaul Process and Parts Support

In general, reparables which become unserviceable at their operational point of use are scheduled for induction into the overhaul production lines at one or more depots. The scheduling is done via a linear programming model operated by the AMC Major Item Data Agency (MIDA), taking into account the quantity to be overhauled over the current 5-year maintenance program planned for the reparable item in question (Reference 2). Each specific maintenance program under which a given number of reparables is to be overhauled or rebuilt is identified by a Procurement Request Order Number (PRON). The reparable item quantity associated with a given PRON is referred to as the "maintenance planned quantity" (MPQ). Increments of the MPQ placed into the overhaul shop at a depot are referred to as induction quantities. The detailed induction schedule for a depot is determined by the "scheduling module" which resides within the SPEEDEX (System Wide Project for Electronic Equipment at Depots Extended) computer system implemented at AMC depots. The MPQ and the induction schedule are updated automatically on a periodic basis.

Repair parts required in support of a PRON are provided through a system made up of the Commodity Command managing the reparable item, the depot's installation supply accounting activity, production planning and control activity, and depot work center stockpoints. SPEEDEX provides parts managers and specialists with information on maintenance and supply transactions and requirements forecasts for a program, including forecasts of part shortages, on a weekly basis or more frequently if necessary. (Reference 3).

Parts management at the Command level is automated under the Commodity Command Standard System (CCSS) which interfaces with the SPEEDEX system. As a result of recent actions initiated by the Director of Maintenance at AMC Headquarters - including this study - depot overhaul related functions

performed by the CCSS and the SPEEDEX system and their functional interrelationships are currently being revised. In general, the CCSS provides a standardized method of processing depot level maintenance program information for organic, commercial, contract or cross service programs so as to provide the best possible basis for establishing wholesale procurement and supply requirements in support of overhaul programs.

Detailed information on the CCSS and SPEEDEX system functions and interfaces in the depot maintenance area is in references 1 through 9.

## 2.2 Forecasting Concepts

Various different methods can be used to estimate repair part requirements for overhaul programs. Most of the requirements for parts used in programs executed at AMC depots are estimated for each program by using the overhaul factor concept. Another approach is the use of the demand rate to estimate the quantity of a given part needed to cover one or more programs concurrently.

The overhaul factor represents the quantity of a given repair part required to overhaul a fixed quantity of a reparable item in a specified condition of unserviceability. The quantity of a part required to overhaul X number of reparables items needing the part is simply X times the overhaul factor when the factor is quoted on a "per one reparable item" basis.

The demand rate represents the quantity of a given repair part needed to cover consumption of the part, per fixed unit of time, in overhaul operations. Using this concept, the quantity of a part required to overhaul X number of reparables is immaterial. Instead, a fixed period of time is used to arrive at a part requirements quantity. The demand rate approach is typically used for parts such as common nuts, bolts, washers, sandpaper, etc., for which recurring demand is fairly steady and independent of the number of reparables overhauled under any specific program as long as the aggregate overhaul workload does not vary significantly with time.

The problem addressed in this study is the determination of the preferred technique for forecasting the overhaul factor needed for repair part requirements estimates.

## 2.3 Assumptions

Major assumptions underlying the study are:

a. Data to update overhaul factor estimates will be collected and processed as required.

b. Any forecasting technique selected must be applicable to all repair parts needed in depot overhaul, regardless of commodity class to which a repair part or a reparable item belongs.

Additional assumptions associated with the various forecasting techniques to be discussed are stated where appropriate.

## 2.4 Study Approach

Available reports and other literature were reviewed to select forecasting techniques which appeared to be especially applicable to the problem at hand. Major Subordinate (Commodity) Commands and depots of the Army Materiel Command were contacted in search of information and actual repair part consumption data. Telephone inquiries were also made with US Air Force and Navy activities. A letter of inquiry concerning overhaul operations was sent to 10 non-military organizations and followed up by telephone calls. (Appendix I) Computer programs were developed to simulate overhaul factor forecasting and to build a suitable data base for simulation purposes. Quantitative measures of forecasting technique performance obtained from the simulation and considerations concerning degree of ease of future implementation and use in the CCSS and SPEEDEX system were defined. These provided a set of criteria for selection of the preferred technique for overhaul factor forecasting.

## CHAPTER III

## DATA BASE AND FORECASTING TECHNIQUES

### 3.1 Literature Search and Review

A custom bibliography on the subject "Forecasting" was obtained from the Defense Logistics Studies Information Exchange (Reference 10). The bibliography listed three papers (References 11, 12 and 13) which reported on work closely related to overhaul factor forecasting. Astrachan and Sherbrooke (Reference 14) report on a study to determine empirically whether the exponential smoothing technique is superior to the moving average technique, using historical data on repair parts of an aircraft and a missile system. Brown (Reference 15) presents complete coverage of a wide variety of forecasting models. Lewis (Reference 16) also presents analyses and illustrative examples of the more frequently applied forecasting techniques including adaptive response rate forecasting proposed by Trigg and Leach (Reference 17). McGlothlin, et al (References 18, 19, 20) studied the use of Bayesian techniques for spare parts demand prediction. Markland (Reference 21) reports on a comparative evaluation of demand forecasting techniques for military helicopter spare parts and presents a comprehensive review of demand prediction research and an extensive bibliography.

Review of literature cited above, consideration of available data, the particular forecasting problem structure and the forecasting techniques used in the CCSS and SPEEDEX system at the time of this study resulted in selection of a set of techniques for evaluation.

Papers by Axtell (Reference 22) and Quinn (Reference 23) are the most recent and closely related to the subject at hand. These papers became available after the data collection, simulation runs and analyses work at IRO had been completed. Axtell used empirical data on repair part consumption from the same source (US Army Electronics Command) which furnished part of the data base for the IRO study. Quinn employed computer simulated repair part demand time series rather than actual data. Both authors provide comparative evaluations of forecasting techniques. Results

obtained by Axtell are, in general, consistent with findings of the study reported herein.

## 3.2 Data Base

The selection and formulation of forecasting techniques was influenced by the type of actual data on repair part usage in depot overhaul programs available for this study. This data had been accumulated by the US Army Electronics Command (ECOM) and the US Army Troop Support Command (TROSCOM) over a five year period (1967 to 1972). ECOM and TROSCOM furnished the data on magnetic tape in so-called ZK and BT1 formats respectively. These formats were prescribed by regulations in effect during that time; details on these are in References 3 and 22. The formats provided the following key data elements: stock number of item being overhauled, PRON serial number and associated fiscal year, identifier of depot performing the overhaul, type of overhaul performed (e.g., either "rebuild" or "complete reconditioning" versus "inspect and repair as necessary"), quantity of the reparable item on which overhaul was completed under the PRON at a given depot, and the stock number and quantity of a given repair part issued against the PRON by the depot's installation supply accounting activity. Regulations did not require the recording of data on the repair part quantity actually used to cover any given reparable item among those overhauled on a given PRON; hence, data of this type was not available.

The ECOM tape contained data on 359 reparable items involving 1522 PRONS and about 30 thousand repair parts. The TROSCOM tape reported on 65 end items involving 230 PRONS and about 26 thousand parts. The raw data base was edited to create a purified data base for subsequent use in computer simulation. This editing accounted for the following conditions:

a. Only non-zero issue quantities of a repair part used on a given end item overhauled under a given PRON were contained in the raw data base tapes. There were many parts used on some PRONs for a given reparable but not on other PRONs for the same reparable item, type of overhaul and

depot. Zero issue quantities were supplied in the purified data base. The assumption was made that if a part was used in performing a specified type overhaul on a given reparable on one or more in a series of PRONs, the part was subject to replacement on the total number of PRONs for that reparable item. The omission of zeros in a time series of issue quantities would have seriously diminished if not invalidated the significance of analysis results obtained. It was also assumed that the repair part issue quantity reported under a given PRON represented the actual quantity consumed to overhaul the reported reparable completion quantity.

b. Reparable items which had experienced fewer than 3 successive PRONs were eliminated. This was done to have repair part issue and reparable item completion observations on at least 3 PRONS, the first of which furnished an initial estimate of the overhaul factor to be updated for the next and subsequent PRONs.

c. Data records not associated with rebuild or complete reconditioning type overhaul were eliminated.

d. Data records flagged by the originator as being unreliable were eliminated.

e. Data records with questionable identification of the reparable item, repair part, Commodity Command or depot were eliminated.

The data purification process yielded a data base with a combined (ECOM and TROSCOM) total of 413 PRONs involving 53 reparable items and 8614 repair parts each of which was used on 3 or more PRONs. Roughly, 60 percent of the total purified data base derived from the original ECOM tape.

### 3.3 Overhaul Factor Forecasting Techniques

Seven forecasting techniques were investigated. Each of these is described in this paragraph under the following generic names:

a. Cumulative History

b. CCSS Model

c. Moving Average on Sums

d. Moving Average On Ratio

e. Single Exponential Smoothing

f. Adaptive Exponential Smoothing

g. Modified Exponential Smoothing

In all of these techniques an overhaul factor forecast is made to estimate the requirements quantity of a given part needed for the next PRON, based on the consumption experience for the part on the same stock numbered reparable item under preceding PRONs. Overhaul factor forecasts cannot be updated during but only upon completion of a PRON. This is because consumption (issue) quantities are recorded and reported on the total number rather than on individual reparable items completed under a PRON.

For ease of subsequent discussions, the overhaul factor is expressed as the quantity of a given repair part required to overhaul one reparable item of a specified type characterized by a unique stock number.

In the simulation, the issue and completion quantity from the first PRON was used to estimate the initial overhaul factor. In actual operations, an engineering estimate posted on initial provisioning documentation is used for the initial overhaul factor estimate. This applies to all techniques to be discussed here.

Cumulative History

This technique was programmed in the SPEEDEX system used exclusively at the AMC depot level. The forecast of the overhaul factor is estimated by the ratio of the cumulative total repair part issue quantities divided by the cumulative total reparable items overhauled on the last and all preceding PRONs. This is an adaptation of the classical time series model with a constant trend and a time dependent error term where the expected value of the error is assumed to be zero over the time period preceding the forecast. (For details of time series models associated with forecasting techniques, refer to References 15, 16, or equivalent sources). Algebraically, using J and K as PRON indices, the forecast of the overhaul factor for the next PRON, based on data

from K preceding PRONs, is given by

$$F(K+1) = \sum_J Q(J) / \sum_J N(J) \quad (1)$$

$$F(1) = \text{Engineering Estimate}$$

$$J = 1,2,\ldots K \ ; \ K = 1,2,3\ldots$$

where

$F(\cdot)$ = overhaul factor, quantity of specified repair part required to overhaul one specified reparable item.

$N(J)$ = quantity of specified reparable item on which overhaul was completed under the Jth PRON

$Q(J)$ = quantity of specified repair part issued (consumed) to complete $N(J)$ reparable items under PRON J.

The SPEEDEX system routine automatically inserts a zero consumption quantity whenever appropriate.

CCSS Model

This technique is unique in that it was not found in any of the literature reviewed except in Reference 6. It is a computational algorithm which, up to a point, works like the cumulative history technique; it then forces a periodic discarding of old data. In a sense, it is a modification of the moving average technique discussed below. The discarding of data is accomplished by the use of two parameters expressed in terms of a minimum and a maximum quantity of the reparable item on which overhaul was completed. As long as the cumulative reparable item completion quantity falls within the range defined by the two parameters, the overhaul factor is updated via the cumulative history technique. The instant when the maximum parameter has been reached or exceeded the overhaul factor

estimate is "frozen" and applied to subsequent completion quantities. When the cumulative number of these completions reaches or exceeds the minimum parameter, the "frozen" factor and associated consumption and completion history is discarded; a new factor is estimated using the cumulative history technique until the maximum parameter is reached again; then the cycle just described starts over again. The forecast of the overhaul factor in one of the cycles may be expressed as follows, assuming forecast was frozen after completion of PMC L:

If: $\sum_{J} N(J) <$ Minimum Parameter:

$$J = L + 1,\ L + 2, \ldots L + K - 1 \qquad (2a)$$

$$F(L+K) = F(L)$$

If: Minimum Parameter $\le \sum_{J} N(J)$

$$F(L+K) = \sum_{J} Q(J) / \sum_{J} N(J) \qquad (2b)$$

If: $\sum_{J} N(J) \ge$ Maximum Parameter

$$F(L+K) = \sum_{J} Q(J) / \sum_{J} N(J) \qquad (2c)$$

Forecast is again frozen at $F(L+K)$ value.

$$F(L) = \text{Engineering Estimate}$$

An illustrative example of forecasting by the CCSS model is included under Appendix 2.

In contrast to the cumulative history technique, the CCSS model requires specification of numerical values of the minimum and maximum parameters. Available documentation provides the following guidance:

"The maximum parameter is established to prevent the (data) file from becoming excessively long. The spread between minimum and maximum parameters should not exceed 1 to 3 years of net capacity quantity. The overhaul parameters must relate to the density of the equipment. For low density equipment, the minimum parameter would be relatively low and the spread between minimum and maximum not too great. As the density of equipment increases, higher minimum parameters and greater spread would normally be advisable. The minimum parameter must be greater than zero and the maximum must be greater than the minimum." (Reference 6)

In simulating forecasting with the CCSS model, the minimum parameter was fixed at one third of the average yearly maintenance program quantity for a given reparable item. The maximum parameter was fixed at values varying between one half and 3 times this quantity. These values were chosen based on inquiries with the AMC Aviation Systems Command.

Moving Average on Sums

Detailed analyses and applications of moving averages are amply documented in the literature (e.g., Reference 15). The particular application of this technique for overhaul factor forecasting is based on the idea that it may be applied separately to the sum in the numerator and the sum in the denominator of the ratio expressing the overhaul factor estimate.

The base period parameter which characterizes the moving average technique can be expressed either in terms of a specified number of PROM's or implied from a specified number of reparable items overhauled. Both of these two models were used in the simulation.

PRON Base Period Model. - Let B denote the number of PRONS representing the moving average base period. Then, with previous notation, the forecast for the next PRON is.

$$F(K+1) = \sum_{J} Q(J) / \sum_{J} N(J) \tag{3a}$$

$$J = 1,2,\ldots,K$$

$$K = 1,2,\ldots B$$

$$F(K+1) = \sum_{J} Q(K+1-J) / \sum_{J} Q(K+1-J) \tag{3b}$$

$$J = 1,2,\ldots B$$

$$K = B+1,\ B+2,\ldots\ldots$$

In the simulation the base period parameter B was assigned integer values in the range from 1 to 6.

Item Completion Base Period Model. - Let B denote a fraction or integer multiple of the average yearly maintenance program quantity described under the CCSS model. Let J, K, and L be PRON indices. The forecasting algorithm may be formulated as follows:

Put L equal to 1 initially. Then, with $J = L, L+1, \ldots K$,

$$\text{i.} \quad \text{if} \quad \sum_{J} N(J) \leq B \text{ , retain current value of } L \tag{4}$$

$$\text{ii.} \quad \text{if} \quad \sum_{J} N(J) > B \text{ , increment current value of } L \text{ by } 1.$$

$$F(K+1) = \sum_{J} Q(J) / \sum_{J} N(J).$$

The range of B as discussed under the CCSS model was used in the simulation.

A numerical example illustrating this algorithm is given in Appendix 2.

Moving Average On Ratio

In this application the moving average technique is applied directly to the ratio of repair part issue quantity to reparable item completion quantity on a given PROM. As in the moving average on sums technique, the base period parameter is expressed either in terms of a specified number of PROMs, or implied from a specified number of reparable items overhauled.

PROM Base Period Model. - Using notation introduced previously with B denoting the number of PROMs representing the moving average base period, the forecasting algorithm may be formulated as follows:

For $K = 1,2,\ldots,B$ and $J = 1,2,\ldots K$

$$F(K+1) = [1/K] \cdot \sum_{J} [Q(J)/M(J)] \tag{5a}$$

For $K = B+1,\ B+2,\ldots.$

$$F(K+1) = F(K) + [1/B] \cdot [Q(K)/M(K) - Q(K-B)/M(K-B)] \tag{5b}$$

In the simulation, the base period parameter was assigned integer values in the range from 1 to 6.

Item Completion Base Period Model. - As before, B denotes a specified fraction or multiple integer of the average yearly maintenance program quantity. The forecasting algorithm may be formulated as follows:

Put L equal to 1 initially. Then, with $J = L, L+1, \ldots, K$,

i. if $\sum_J N(J) \leq B$, retain current value of L (6)

ii. if $\sum_J N(J) > B$, increment value of L by 1.

$$F(K+1) = [1/(K+1-L)] \cdot \sum_J [Q(J)/N(J)]$$

Thus, the integer base period K+1-L is, by virtue of the determination procedure for L, a function of the reparable item completion quantities on successive PRONS with PRON index L through K.

Single Exponential Smoothing

Many analyses and illustrative examples of exponential smoothing are provided in the literature (e.g., Reference 15). The use of higher order exponential smoothing (as well as higher order moving averages) would have added to the degree of completeness and sophistication of this study. However, the additional work and time expenditure appeared not to be justified in view of the variability and general nature of the basic data.

The well-known (Reference 15) relationship between the base period parameter of the moving average technique and the smoothing constant required by the exponential smoothing technique rests on the equivalence of data age or equivalence of variance of forecast estimates produced by these two techniques. This relationship, stated here for ready reference is

$$a = \frac{2}{B+1} \tag{7}$$

where

a = smoothing constant, $0 < a < 1$

B = moving average (integer) base period parameter.

The smoothing constant was chosen by application of equation 7 to correspond to the range of B used in the simulation.

The forecast of the overhaul factor for the next PROM is given by

$$F(K+1) = [a]\cdot[Q(K)/N(K)] + [1-a]\cdot[F(K)] \qquad (8)$$

$$K = 1, 2, \ldots .$$

<u>Adaptive Exponential Smoothing</u>

Analyses and examples of this forecasting technique can be found in References 16 and 17. The basic idea is to vary the smoothing constant automatically as a function of statistical characteristics of the series of forecasts and actual observations. In the context of the overhaul process, if successive observations on the Q/N ratio are numerically relatively stable, the smoothing constant "a" should be small so that small perturbations in the ratio are prevented from being unduly amplified thus producing unwarranted large fluctuations in the forecasts. On the other hand, if the Q/N ratio is highly variable, the forecast made for the last PROM is most likely not too representative of what happens on the next PROM; hence, "a" should be relatively large which makes the forecast more responsive to the latest observation available. The way in which this can be accomplished is to use the absolute value of a ratio referred to as "Trigg's tracking signal" (Reference 16) instead of a fixed smoothing constant for producing forecasts. This signal is defined as the exponentially weighted average of the forecasting error divided by the mean absolute deviation. The weighted average of the forecasting error, EAVG is defined as

$$EAVG\ (K+1) = [a]\cdot[E(K)] + [1-a]\cdot[EAVG(K)] \qquad (9)$$

where

$$E(K) = F(K) - Q(K)/N(K) \qquad (10)$$

The mean absolute deviation, MAD, is defined as

$$MAD(K+1) = [a] \cdot [|E(K)|] + [1-a] \cdot [MAD(K)] \tag{11}$$

Trigg's tracking signal, T, is then given by

$$T(K+1) = EAVG(K+1)/MAD(K+1) \tag{12}$$

Let AVT denote the absolute value of T. Then, the forecast of the overhaul factor based on data from K PRONs is

$$F(K+1) = [AVT(K+1)] \cdot [Q(K)/N(K)] + [1-AVT(K+1)] \cdot [F(K)] \tag{13}$$

In the simulation, the smoothing constant "a" required to compute EAVG and MAD was chosen as explained under (7) above.

Modified Exponential Smoothing (Modexpo)

This technique was developed in the course of this study. The modification of the (single) exponential smoothing technique is in the determination of the smoothing constant which weights the most recent observation. The Modexpo technique is designed so that, for example, more weight is given to a repair part issue quantity observation associated with 10 reparable item completions than to an issue quantity associated with only 5 reparable item completions.

The general development of this technique is documented in Reference 24. A brief summary of the development in terms of notation used in this report is given in Appendix 3 for ready reference. The algorithm for producing overhaul factor forecast involves the concept of "average yearly maintenance program quantity" computed in a particular way.

Let P denote the average yearly maintenance program quantity. Define P by

$$P = [[ \frac{\text{Prior MPQ} + \text{Execution MPQ} + \text{Target MPQ}}{N} ]] \qquad (14)$$

where

Prior MPQ = Actual quantity of given reparable item on which overhaul of specified type was completed during prior fiscal year.

Execution MPQ = Quantity of given reparable item scheduled to be overhauled in current fiscal year.

Target MPQ = Quantity of given reparable item scheduled to be overhauled in next fiscal year.

N = Number of fiscal years with MPQ greater than zero.

[[X]] = Value of X rounded to nearest integer.

$$P = 0 \text{ if Execution MPQ} + \text{Target MPQ} = 0. \qquad (15)$$

The overhaul factor forecast based on observations from K completed PRCMs is given by

$$F(K+1) = [1-W] \cdot [Q(K)/N(K)] + [W] \cdot [F(K)] \qquad (16)$$

where

$$W = (11/13)^{N(K)} \text{ if } P = 1,2,...12$$
$$W = (P-1/P+1)^{N(K)} \text{ if } P = 13,14,.... \qquad (17)$$

A summary of the development of (11) is given in Appendix B.

The definition of the average yearly program quantity, P, assures that past variations in maintenance program quantities will be phased out in yearly updates of P. When P is zero, the latest forecasted factor is frozen and retained on file. Forecasts are made only if P is larger than zero for a given reparable item.

The value of P for any given reparable item is readily obtainable through MIDA and [illegible] computer programs. Thus, the parameter needed to apply this forecasting technique can be computer generated.

In the simulation, P was computed by dividing the total number of completions on a reparable item in the purified 5-year data base by 5 and then using multiples of this value.

## CHAPTER IV

## EVALUATION CRITERIA AND SIMULATION PROGRAM

### 4.1 Evaluation Criteria

Criteria to identify the preferred technique for overhaul factor forecasting are expressed in terms of desirable properties of the technique from a comprehensive viewpoint of depot overhaul process management and operations; this includes considerations of data requirements, data availability and data processing in the computerized systems for maintenance program planning at MIDA and in the CCSS and SPEEDEX system. Four properties were identified as characterizing a good forecasting technique: Produce small forecast errors. Produce small negative deviations. Require small data storage capacity. Enable automatic determination of forecast model parameters.

Descriptions of the terms "forecast error" and "negative deviation" and rationale for choosing these particular properties as evaluation criteria are summarized below. Computational algorithms for determining the error statistics, i.e., the quantitative magnitudes of forecast error and negative deviation are presented in paragraph 4.2.

Forecast Error

The forecast error is expressed in terms of the mean absolute deviation. In general, the deviation is the difference between a forecasted value and the corresponding actual value observed on the variable of interest; e.g., the overhaul factor forecasted and the actually observed ratio of repair part issue quantity to reparable item completion quantity for a PROM. The average of the absolute value of the deviation over a number of observations is the mean absoluted deviation (MAD). Small MADs minimize over- or under-estimation of repair part requirements. At the depot level, this reduces the chances of stockout on the one hand and repair part excesses on the other. Usually, supply safety level stock requirements increase with increasing demand variability. At the NICP level, a smaller forecast error associated with that portion of the total demand for the repair part due to overhaul programs has a corresponding incremental cost effect on the wholesale supply safety stock investment required for a fixed level of supply performance.

Negative Deviation

This term denotes the quantity by which the actually observed value exceeds the corresponding forecasted value. It is a measure of the degree of underforecasting. The smaller the tendency of a forecasting technique to underestimate repair part requirements, the smaller will be the probability of experiencing stockout conditions during an overhaul program. Usually, such stockouts result in a temporary stopping of the overhaul production line until the needed part becomes available. These "line-stopper" events are considered more costly, in the long run, than the cost of carrying more stock of the repair part in inventory; this is especially true in those cases where high-priced or urgently required reparable items are being overhauled.

Data Storage and Processing Requirements

Advantages of minimal data storage and processing requirements are obvious. They are especially relevant in the CCSS and SPEEDEX system environment. In addition to other functions performed by these systems, the multitude of reparable items and repair parts and the multiple number of depot maintenance facilities involved in the overhaul process call for reducing information storage on file or disk and reduction of computer processing time requirements wherever possible.

Automatic Determination of Model Parameter

The advantages of the ability to determine forecasting model parameters - such as the base period or smoothing constant - from empirical information generated by the process for which forecast are being made are generally recognized.[1] Among the techniques discussed in this report only the cumulative history technique does not require a parameter. Under

---

[1] See discussion on adaptive smoothing in paragraph 3.3 and related references.

the Modexpo technique, the required smoothing constant is automatically determined from data on the maintenance program and reparable item completion quantities.

The determination of the minimum and maximum parameter in the CCSE model is left up to the more or less subjective ideas of a number of individuals (see paragraph 3.3). It appears that the resulting parameter values would reflect a choice made on a basis not less arbitrary than that explicitly exhibited in the determination of the "small program quantity" parameter associated with the Modexpo forecasting technique.

Under adaptive exponential smoothing, the smoothing constant is fixed automatically through a transformation of actual observations on the process being forecasted.

## 4.2 Simulation Logic and Error Statistics

The computer program was developed to simulate production of sequential overhaul factor forecasts based upon the consumption (Q) of a given repair part and reparable item completion (N) quantities recorded at each depot. The program was designed to operate in two modes, the NICP mode and the Depot mode. Salient features of each mode may be summarized as follows.

Under the NICP mode, the receipt and processing of reports with Q and N data furnished by each depot upon completion of a PRON were simulated. The Q and N pairs were put into one array by increasing order of fiscal year of PRON completion. The BT1 report format does not provide data on the starting or completion date of a PRON at any depot; it only gives the fiscal year in which the PRON serial number was originated. Thus, the Q and N array constructed for the simulation only approximates the time series which actually generates at an NICP with sequential eceipts of BT1 transactions. Using the Q and N array the program then produces overhaul factor forecasts and associated error statistics under the selected techniques for each repair part consumed on successive PRONs. The first Q and N pair in the array for a given part furnished the Q/N ratio used as initial value of the forecasted factor, F(1), since actual engineering estimates were not available. Additional modifications of the data based for these runs were made; for example, data on only those reparable items were used which had been overhauled at at least two different depots.

Under the Depot mode, the O and N pairs were put into arrays kept separately for each depot and sequenced by PRON fiscal year. Overhaul factor forecasts and associated error statistics were generated for successive PRONs at individual depots.

The error statistics obtained from runs under the Depot mode showed consistently better results than those obtained under the NICP mode, using the ECOM data (see Appendix 2, Table A-1). With TROSCOM data, the MAD results were worse but the negative deviation (NEGDEV) results were better under the Depot mode than under the NICP mode. Since the ECOM data represented 80 percent of the total data base it was decided to use the Depot mode for forecasting technique comparison and evaluation. This decision was further influenced by a recommendation in a study conducted at the AMC Tank Automotive Command (Reference 26) to the effect that overhaul factor forecasting using consumption data should be done exclusively at the depots.

Formulas for the error statistics are exhibited below. In general, the evaluation runs proceeded as follows. A particular forecasting technique and associated model parameters were chosen. O and N values for a given repair part and PRONs on a given reparable item were read from the data array. Successive forecasts were made and the actual O/N ratio for each PRON was computed. To achieve a fairer comparison between techniques, data on the first 3 PRONs were used only to establish initial forecasts F(1), F(2), and F(3) before computing the error statistics (MAD and NEGDEV) based on the number of the remaining PRONs on which the part was used. MAD and NEGDEV values were saved. Data on the next repair part was then picked up and the process repeated until all eligible repair parts (those having experienced at least 3 PRONs on a given reparable item) were accounted for. The accumulated MAD and NEGDEV values were then divided by the total number of eligible parts. This yielded the overall average MAD and NEGDEV values for the particular technique and model parameters under evaluation. The process was then repeated for the remaining techniques and model parameters. Two sets of error statistics were used in the evaluation runs.

In the first set, the statistics are based on the difference between forecasted and the actually observed repair part issue (consumption) quantity for one PRON.

Let $\hat{Q}(J,K) = F(J,K)] \cdot [N(K)]$ denote the consumption quantity of a given repair part identified by index j forecasted for PRON K. Define the overhaul factor deviation D, observed on this part on PRON K by

$$D(J,K) = [\hat{Q}(J,K) - Q(J,K)]/N(K) \tag{18}$$

Let NP(J) denote the total number of PRONs on which the repair part was consumed to overhaul a given reparable item. Data on the first 3 of these PRONs produces initial overhaul factor forecasts F(J,1), F(J,2) and F(J,3) under a given technique. The mean absolute deviation for this repair part is then given by

$$MAD(J) = [\sum_{K} D(J,K)]/[NP(J)-3] \tag{19}$$

$$K = 4,5,\ldots NP(J)$$

Define

$$\begin{aligned} A(J,K) &= D(J,K), \text{ if } A(J,K) < 0 \\ &= 0, \text{ otherwise} \end{aligned} \tag{20}$$

The mean negative deviation, NEGDEV, for this repair part is then given by

$$NEGDEV(J) = \sum_{K} A(J,K) \tag{21}$$

The MAD(J) and NEGDEV(J) values are then averaged over the total number of eligible repair parts, JTOTAL; viz.,

$$MAD = [\sum_J MAD(J)]/JTOTAL \quad (22)$$

$$NEGDEV = [\sum_J NEGDEV(J)]/JTOTAL \quad (23)$$

$$J = 1,2,\ldots JTOTAL$$

The second set of error statistics is based on the difference between forecasted and actually observed repair part quantities for 2 successive PRONS: viz.,

$$D(J,K) = \frac{[\hat{Q}(J,K) + \hat{Q}(J,K+1) - Q(J,K) - Q(J,K+1)]}{N(K) + N(K+1)} \quad (24)$$

where

$$\hat{Q}(J,K) + \hat{Q}(J,K+1) = [F(J,K)]\cdot[N(J,K) + N(J,K+1)] \quad (25)$$

Thus,

$$D(J,K) = F(J,K) - [Q(J,K) + Q(J,K+1)]/[N(J,K) + N(J,K+1)] \quad (26)$$

The corresponding MAD and NEGDEV values are then given by equations 19 through 23 with the appropriate range of PRON index K. It was felt that this set of error statistics would smooth out some of the variation in deviations and serial correlation in consumption quantities between successive PRONs. In addition, it was desired to obtain some indication of the ability to forecast longer term averages of the PRON consumption quantities. It is noted that if the consumption quantities on successive PRONs are exactly proportional to the respective completion quantities, the magnitude of deviation given by equation 24 is the same as that given by equation 18.

# CHAPTER V

## RESULTS AND FINDINGS

### 5.1 Results From Inquiries

Information on overhaul operations and practices obtained through inquiries with other military services and non-military organizations (see Appendix 1) is summarized in this paragraph.

The Air Force had used the recurring demand approach to requirements forecasting for overhaul almost exclusively in the past. Demands for a repair part due to overhaul programs were not treated separately from demands arising from other support requirement. Advanced Logistic System Procedures now provide the option to use overhaul factors.

The Navy has not instituted standard procedures but like the Air Force has programmed the capability to use overhaul factors. The Naval Aviation Supply Office uses an engineering estimate produced under initial provisioning procedures for determining initial overhaul requirements. After the demand development period (approximately 2 years after the initial operational capability date for an end item) the initial factor is phased out. Subsequent repair part requirements for overhaul programs are treated as recurring demands and repair part supply levels are established on the basis of recurring demand history.

It appears that there has been no definitive completed study on the choice between application of the overhaul factor and the recurring demand approach. In effect, Air Force, Navy and Army practices leave the choice as to which approach to use up to the individual inventory control points.

Inquiries with airline, railroad, automotive and marine organizations yielded information which may be summarized as follows. Automotive vehicle fleet operators such as trucklines and the U.S. Postal Service, and producers of automotive vehicles do not overhaul their vehicles on a programmed basis. Repair or rebuild is done as required by the condition of the vehicle(s) at any point in time. A trend of increasing use of installed monitoring devices to detect need for repair or overhaul

is apparent. Airline, railroad and marine shipping companies have formal overhaul programs as required by government regulations. Repair part consumption factors are estimated based on subjective combinations of past experience, engineering judgement and policy decisions arrived at in a more or less structured fashion. Some airlines and the U.S. Postal Service make use of the moving average technique to update repair part consumption estimates.

## 5.2 Simulation Results

Forecasted overhaul factors obtained by the cumulative history (SPEEDEX), the TCSA Model and the Medempe technique applied to the consumption history of a given part over a series of PRONs for a given end item are plotted in Figure 1. The actual factor, i.e., the ratio $Q(K)/N(K)$ corresponding to forecast $F(K)$ for PRON $K$ is also plotted. Successive values have been connected by straight lines for illustrative purposes. The general pattern exhibited by actual and forecasted factors is typical of repair part and reparable item overhaul program historical records in the ECOM and TROSCOM data.

Percentage values of the overall mean absolute deviation and the negative deviation obtained from ECOM overhaul program data with applications of equations 18, 22 and 23 and those obtained from TROSCOM data with applications of equations 20, 22 and 23 are tabulated in Table 1 for each of the forecasting techniques and model parameter evaluated.

## 5.3 Discussion of Results

The mean absolute deviation values posted in Table 1 under the column labelled "ECOM DATA" differ considerably from corresponding values for the TROSCOM data. This is an indication of the difference between the two commodity groups in terms of repair part requirements for overhaul of reparable items as reflected in the available data. For example, the overall average overhaul factor for ECOM items is about 9 and that for TROSCOM

about 32 per 100 completions.

Within either of the two commodity groups, the adaptive exponential smoothing technique shows the worst and the modified exponential smoothing the best performance in terms of the mean absolute deviation. Based on the average of values posted in Table 1 for each technique and corresponding model parameters, the MAD under Modexpo is 11.45 from ECOM data and 62.85 from TROSCOM data. The corresponding MAD values under Adaptive Exponential Smoothing are 14.46 and 91.85 respectively. The standard deviation of the difference between MADs produced by two different techniques applied to the ECOM data is on the order of 0.2. Thus, the MAD differences observed are not insignificant.

In terms of the negative deviation values in Table 1, the Adaptive Exponential Smoothing technique performs better than any other technique applied to ECOM data but is surpassed by the Moving Average On Sums technique applied to TROSCOM data, on the average. The CCSS Model performs the worst in this sense. Modexpo does better than the Cumulative History technique but not as well as the CCSS Model when applied to ECOM data. The opposite of this is true where these techniques are applied to TROSCOM data. Thus, the negative deviation results are somewhat inconclusive.

It is noted that Axtell (Ref. 22) found the Cumulative History technique to perform worst and a technique (Quadratic 3) incorporating completion history in a special way to perform best under his evaluation criteria.

It was desired to compare the Cumulative History, the CCSS Model and the Modexpo technique based on the error statistics obtained with maintenance program parameter values of 1 and 2 years. For this purpose, a "percent improvement indicator", PI, was defined as follows:

$$\text{Statistic } PI(X) = \left[\frac{X-Y}{X}\right]\cdot[100] \tag{27}$$

where

X = value of statistic generated by technique X
Y = value of statistic generated by Modexpo

and where "statistic" is either the MAD or NEGDEV computed from values posted in Table 1. Data used and results of this comparison are tabulated in Table 2.

With reference to Table 2, it can be seen that for the results obtained with ECOM data, Modexpo provides a 6.1% reduction in MAD and a 2.7 % reduction in NEGDEV compared to the Cumulative History (SPEEDEX) techniques. Based on TROSCOM data, there is a 1.1% reduction in MAD but a 3% increase in NEGDEV.

In comparison with the CCSS Model, Modexpo provides a 1.3% reduction in MAD and no reduction in NEGDEV, based on ECOM data. Based on TROSCOM data, there is a 6.9% reduction in MAD and 2.8% reduction in NEGDEV.

The advantages offered by Modexpo over the Cumulative History (SPEEDEX) and the CCSS Model technique may be summarized by forming weighted averages of the MAD and NEGDEV percent improvement indicator values. The percentages of the total data in the combined ECOM and TROSCOM data base are used as the relative weights; i.e., 80% for ECOM and 20% for TROSCOM (See Chapter III).

Modexpo vs Cumulative History Technique

Average Improvement In MAD $= [0.8]\cdot[6.1] + [0.2]\cdot[1.1] = 5.1\%$

Average Improvement In NEGDEV $= [0.8]\cdot[2.7] + [0.2]\cdot[-3.0] = 1.6\%$

Modexpo vs CCSS Model Technique

Average Improvement In MAD $= [0.8]\cdot[1.3] + [0.2]\cdot[8.9] = 2.8\%$

Average Improvement In NEGDEV $= [0.8]\cdot[0] + [0.2]\cdot[2.8] = 0.6\%$

Results obtained with the ECOM and TROSCOM data indicate that a reduction in the magnitude of the base period or equivalent smoothing constant is generally accompanied by a reduction in forecast error (MAD). In the case of the Modexpo technique, the one-year average maintenance program value yielded the best result. From the implementation point of view, this value is also considered to maintain a

reasonable degree of stability in the forecasting and requirements determination process.

Data for updating overhaul factor forecasts originates and is processed and quality controlled at the depots where overhaul work is actually accomplished. It became apparent that overhaul factor forecasts developed routinely at a given depot could be furnished directly to the cognizant Command and there combined with forecasts developed at another depot for the same repair part, reparable item and type of overhaul. This would eliminate the transmittal of voluminous original consumption data to the Command; it would also eliminate the need for a second processing operation at the Command on the data already processed once at the depots. A good estimate of the "Command Overhaul Factor" (COF) based on individual "Depot Overhaul Factors" (DOFs) could be developed as follows;

Let n denote the depot at which an overhaul factor, DOF(n), for given repair part, reparable item and type of overhaul has been forecasted. Let P(n) denote the average yearly maintenance program quantity for the nth depot. Then, if there are ND depots producing forecasts of the overhaul factor for the repair part managed by a given Command,

$$COF = \Big[ \sum_{n} (DOF(n)) \cdot (P(n)) \Big] / \sum_{n} P(n) \qquad (28)$$

$$n = 1, 2, \ldots ND.$$

5.4 Conclusions

Based on the evaluation criteria with particular emphasis on reduced data storage and processing time and the automatic determination of model parameters, the Modified Exponential Smoothing technique is the preferred alternative among those considered. Regardless of which technique is chosen, forecast errors will remain large due to the great variability in repair part consumption exhibited by the actual data on the overhaul process.

### 5.5 Recommendations

Findings and considerations described above lead to the recommendation to replace the Cumulative History Technique for overhaul factor forecasting under the SPEEDEX system by the Modified Exponential Smoothing technique with a 1-year average maintenance program quantity as the preferred model parameter.

The practice of double processing of depot overhaul consumption data should be discontinued. Instead, Command level overhaul factors should be estimated from depot produced overhaul factors by means of a weighted average as defined in equation 2[illegible] or equivalent.

Note: Above stated recommendations have already been implemented at the time of this writing. The second recommendation had previously been made in various forms (see References 26 and 27).

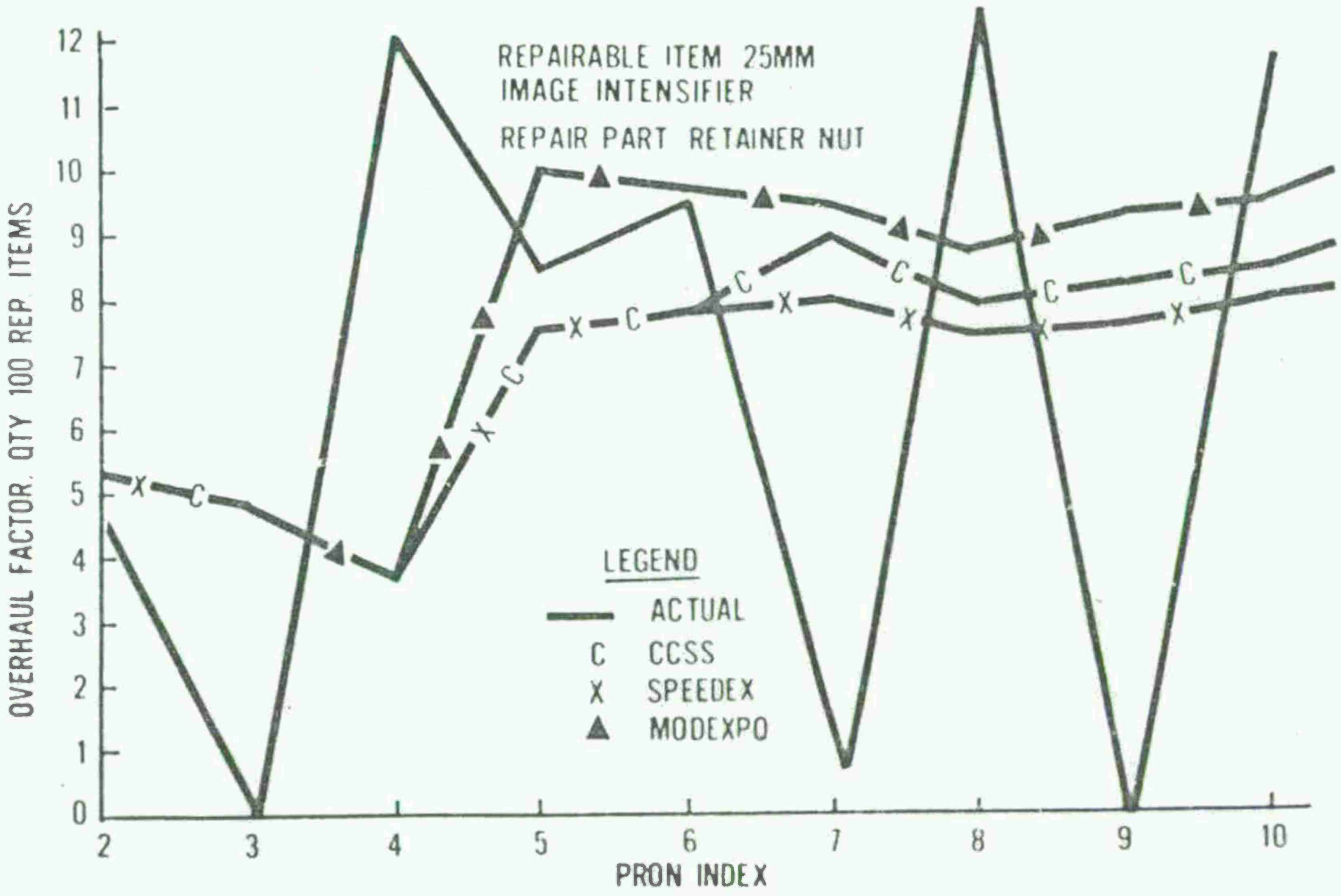


FIGURE 1. ACTUAL AND FORECASTED OVERHAUL FACTORS

| FORECASTING TECHNIQUE | MODEL PARAMETERS | MEAN ABSOLUTE DEVIATION ECOM DATA | MEAN ABSOLUTE DEVIATION TROSCOM DATA | NEGATIVE DEVIATION ECOM DATA | NEGATIVE DEVIATION TROSCOM DATA |
|---|---|---|---|---|---|
| Cumulative History | None | 12.2 | 63.6 | -5.5 | -40.3 |
| CCSS Model | Min. = 1/3 Year<br>Max. = 1/3 Year | 11.3 | 68.4 | -5.3 | -44.2 |
| | Max. = 1/2 Year | 11.3 | 67.5 | -5.3 | -44.8 |
| | Max. = 1 Year | 11.8 | 67.6 | -5.3 | -44.7 |
| | Max. = 2 Years | 11.4 | 70.4 | -5.4 | -43.9 |
| | Max. = 3 Years | 11.9 | 64.2 | -5.4 | -44.2 |
| Modified Exponential Smoothing | Maint. Program | | | | |
| | P = 1 Year | 11.3 | 63.9 | -5.3 | -42.0 |
| | P = 2 Years | 11.6 | 61.8 | -5.4 | -41.0 |
| Single Exponential Smoothing | Smoothing Const. | | | | |
| | a = 0.67 | 11.7 | 67.9 | -5.4 | -41.8 |
| | a = 0.50 | 12.1 | 67.5 | -5.4 | -41.1 |
| | a = 0.29 | 13.0 | 65.4 | -5.5 | -40.9 |
| Adaptive Exponential Smoothing | Smoothing Const. | | | | |
| | a = 0.67 | 13.3 | 82.8 | -5.3 | -41.4 |
| | a = 0.50 | 14.2 | 91.1 | -5.1 | -40.7 |
| | a = 0.29 | 15.7 | 101.6 | -5.0 | -38.9 |
| Moving Average On Sums | Base: 1 PRON | 11.6 | 68.4 | -5.5 | -44.2 |
| | 2 PRONs | 11.4 | 61.7 | -5.3 | -41.1 |
| | 3 PRONs | 12.1 | 64.8 | -5.4 | -40.4 |
| | 6 PRONs | 12.3 | 63.6 | -5.4 | -40.3 |
| | Maint. Program: | | | | |
| | 1/3 Year | 11.2 | 68.4 | -5.3 | -44.2 |
| | 1/2 Year | 11.5 | 67.6 | -5.3 | -41.1 |
| | 1 Year | 11.5 | 58.1 | -5.4 | -42.1 |
| | 2 Years | 11.9 | 62.5 | -5.5 | -40.7 |
| | 3 Years | 12.1 | 63.8 | -5.5 | -40.4 |
| Moving Average On Ratio | Base: 1 PRON | 11.6 | 68.4 | -5.5 | -44.2 |
| | 2 PRONs | 11.8 | 70.1 | -5.5 | -41.7 |
| | 3 PRONs | 12.4 | 72.9 | -5.5 | -40.8 |
| | 6 PRONs | 12.7 | 69.8 | -5.5 | -40.6 |
| | Maint. Program | | | | |
| | 1/3 Year | 11.4 | 68.4 | -5.4 | -44.2 |
| | 1/2 Year | 11.5 | 66.9 | -5.3 | -41.8 |
| | 1 Year | 11.5 | 59.9 | -5.3 | -43.2 |
| | 2 Years | 11.8 | 70.7 | -5.5 | -41.2 |
| | 3 Years | 12.5 | 70.0 | -5.6 | -40.9 |

TABLE 1. MEAN ABSOLUTE AND NEGATIVE DEVIATION FROM FORECASTING TECHNIQUE SIMULATION, PERCENT

| FORECASTING TECHNIQUE | PARAMETERS AVERAGES INDICATORS | MEAN ABSOLUTE DEVIATION | | RELATIVE DEVIATION | |
|---|---|---|---|---|---|
| | | ECOM DATA | TROSCOM DATA | ECOM DATA | TROSCOM DATA |
| Cumulative History | None | 12.[illegible] | 6[illegible].3 | -[illegible] | -40.3 |
| | Average | 12.[illegible] | 63.[illegible] | -[illegible] | -[illegible] |
| | PI | 0.1 | [illegible].1 | [illegible] | -[illegible] |
| CCSS Model | P = 1 year | 11.[illegible] | 67.[illegible] | -[illegible] | -[illegible] |
| | P = 2 years | 11.[illegible] | 70.[illegible] | -[illegible] | -[illegible] |
| | Average | 11.[illegible] | 69.0 | -5.3[illegible] | -[illegible] |
| | PI | 1.[illegible] | [illegible].9 | 0 | 2.[illegible] |
| Modified Exponential Smoothing | P = 1 year | 11.[illegible] | 6[illegible].[illegible] | -[illegible] | -[illegible] |
| | P = 2 years | 11.6 | 61.[illegible] | -5.4 | -[illegible]1.0 |
| | Average | 11.[illegible] | 6[illegible].[illegible] | -5.[illegible] | -[illegible]1.5 |
| | PI | 0 | 0 | 0 | 0 |

TABLE [illegible]. PERFORMANCE COMPARISON OF SELECTED FORECASTING TECHNIQUES, PERCENT

## APPENDICES

**DEPARTMENT OF THE ARMY**
**USAMC INVENTORY RESEARCH OFFICE-USALMC**
**FRANKFORD ARSENAL-PHILADELPHIA, PA. 19137**

REPLY TO ATTENTION OF:
SARFA-AMCIRO

10 April 1974

Dear

We are doing a study for the Army Materiel Command on maintenance practices. The particular area we are now looking into is the area of overhaul. What we are interested in are the policies and practices you follow and general information of how well they have been working for you.

Our specific questions are:

1. Do you have a formal overhaul program for complete aircrafts? for major components?

2. If so, how is overhaul scheduling done? How are items selected to be overhauled?

3. How long before beginning of program execution is the size of the overhaul program fixed?

4. What are your rules for allowing changes to the overhaul schedule once it is developed?

5. How do you forecast the range and quantity of parts needed to support overhaul schedules? Who does this?

6. How long before the start of an overhaul program do you require the parts to be on hand?

7. How long on the average does it take to overhaul an item? (from time of induction until time of completion)

SARFA-AMCIRO 10 April 1974

TO: Mr. Henry Fall

8. Do you do any pre-inspection of items prior to overhaul as an aid to prediction of parts need? If so, how far in advance of the start of the overhaul schedule?

If you cannot provide the answers to these questions, I would appreciate your passing our query along to the proper party. If you'd like any further information, please call me at 215-831-6934.

Sincerely yours,

BERNARD B. ROSENMAN
Director, AMC Inventory Research Office
Institute of Logistics Research
US Army Logistics Management Center

## LIST OF NON-MILITARY ORGANIZATIONS CONTACTED

American Airlines, Inc., New York, N.Y.

Caterpillar Tractor Company, Peoria, Ill.

Chemical Leaman Tank Lines, Inc., Downingtown, Pa.

Douglas Aircraft Company, Los Angeles, Cal.

Matson Navigation Company, San Francisco, Cal.

Pacific Intermountain Express Company, Oakland, Cal.

Penn Central Transportation Company, Philadelphia, Pa.

Southern Railway System, Washington, D.C.

United Airlines, Inc., San Francisco, Cal.

U.S. Postal Service, Washington, D.C.

## APPENDIX 2

## EXAMPLES

### [illegible]ESS Model

This example illustrates the algorithm defined in expressions (2a), (2b) and (2c) under paragraph 4.4.

Suppose the minimum and maximum parameters are 5 and 50, respectively.

Assume the forecast was frozen with completion of the 10th PRON; i.e., L=10. The forecast for the next PRON with index L+K = 10+1 = 11 is F(11) = F(10). Suppose now that 4 reparables are completed under PRON 11; hence, N(11) = 4. This is less than the minimum parameter of 5. Therefore, the forecast for the next PRON, i.e., for PRON 12 is (F12) = F(10). The value of N(11) and the consumption quantity of the repair part under consideration, Q(11), are saved. Assume that 25 reparable items are completed under PRON 12. Then, N(11) + N(12) = 29; this is larger than the minimum parameter but less than the maximum parameter. The frozen factor, F(10), is discarded and the forecast for the next PRON, i.e., for PRON 13 is given by F(13) = [Q(11) + Q(12)]/[N(11) + N(12)].

Assume that 30 reparable items are completed under PRON 13. Then, N(11) + N(12) + N(13) = 59; this is larger than the maximum parameter of 50. The forecast for the next PRON, i.e., for PRON 14 is given by F(14) = [Q(11) + Q(12) + Q(13)]/[N(11) + N(12) + N(13)]. F(14) becomes the new frozen value. Consumption and completion history on PRONS 11, 12, and 13 is deleted from records and a new cycle starts with 14 as the new value for index L. Note that the minimum and maximum parameters are not changed once they are fixed.

### Moving Average on Sums-Item Completion Model

Suppose B = 2, N(1) = N(2) = N(3) = 1. Let L = 1, K = 1; then $\sum_J$ N(J) = 1 < B and F(2) = Q(1)/N(1). Let K = 2; then $\sum_J$ N(J) = 2 = B, and F(3) = Q(1) + Q(2)]/[N(1) + N(2)]. Let K = 3; then $\sum_J$ N(J) = 3 > B. Increment L from L = 1 to L = 2; then, J = 2,3 and F(4) = [Q(2) + Q(3)]/[N(2) + N(3)]; etc.

| FORECASTING TECHNIQUE | ECOM DATA BASE: MEAN ABSOLUTE DEV. | | ECOM DATA BASE: NEGATIVE DEVIATION | | TROSCOM DATA BASE: MEAN ABSOLUTE DEVIATION | | TROSCOM DATA BASE: NEGATIVE DEVIATION | |
|---|---|---|---|---|---|---|---|---|
| | NICP MODE | DEPOT MODE | NICP MODE | DEPOT MODE | NICP MODE | DEPOT MODE | NICP MODE | DEPOT MODE |
| CUMULATIVE HISTORY | 12.5 | 12.2 | -6.[illegible] | -6.5 | 36.6 | 42.4 | -15.[illegible] | -14.5 |
| MOVING AVERAGE ON SUMS | 12.8 | 12.1 | -6.6 | -6.4 | 39.2 | 41.7 | -15.2 | -14.5 |
| MOVING AVERAGE ON RATIO | 12.7 | 12.3 | -6.7 | -6.4 | 37.1 | 40.[illegible] | -15.6 | -14.4 |
| CCSS MODEL | 12.4 | 12.2 | -6.9 | -6.5 | 39.9 | 41.7 | -15.1 | -14.4 |

TABLE A-1. FORECAST ERROR STATISTICS - NICP MODE VS DEPOT MODE, PERCENT

## APPENDIX A

## MODEXPO AND SMOOTHING CONSTANT W

This appendix sketches the development of equations 16 and 17 in terms of notational convention and terminology used throughout this report.

### Modexpo Development

Suppose that in completing overhaul of a group of $N$ reparable items under a given PRON the repair part quantity actually consumed on each individual item is recorded. Assume that the initial overhaul factor forecast used to predict the repair part requirements for the total of $N$ reparable items is updated whenever one of the items under this PRON is completed. Denote the consumption quantity observed and recorded on the nth reparable item by $C_n$. Suppose the single exponential smoothing technique with smoothing constant "a" is used to update the forecast after each observation. The last of these updates will reflect $C_N$, i.e., the consumption recorded on the Nth reparable item; this last update of the overhaul factor will then be used to predict the repair part requirement for the next PRON on the given reparable item. Let $F_o$ denote the initial overhaul factor estimate prior to completion of the first reparable item on the Kth PRON so that $F_o = F(K)$ in our notation. Using consumption experience $C_n$ and single exponential smoothing, the updated factor, $F_n$, based on a series of n observations, i.e., on $C_1$, $C_2$, ...$C_n$, is

$$F_n = a \cdot C_n + (1-a) \cdot F_{n-1} \qquad \text{(A.1)}$$

$$n = 1,2,\ldots N \; ; \; 0 < a < 1$$

An equivalent expression for $F_n$ is (Reference 16)

$$F_n = (1-a)^n \cdot F_o + a \cdot \sum_i (1-a)^{n-i} \cdot C_i \qquad \text{(A.2)}$$

$i = 1,2,\ldots n$

The updated factor based on the total of N observations when all N reparable items under PRON K have been completed is $F_N$; this now becomes the overhaul factor forecast for the next PRON on the same reparable item. In our notation, $F_N = F(K+1)$; also, $Q(K)$, the cumulative issue quantity is assumed to be equal to the cumulative consumption of a given part on PRON K under which $N(K)$ reparable items were completed; thus,

$$Q(K) = \sum_n C_n \qquad \text{(A.3)}$$

$n = 1,2,\ldots N(K)$

Data is available only on $Q(K)$ and $N(K)$ but not on the $C_n$; however, $C_n$ may be approximated by using the average value, C, where

$$C = Q(K)/N(K) \qquad \text{(A.4)}$$

With this approximation A.2 can be written as

$$F_n = (1-a)^n \cdot F_o + a \cdot C \cdot \sum_i (1-a)^{n-i} \qquad \text{(A.5)}$$

$i = 1,2,\ldots n$

To simplify this expression put $k = i - 1$ and use the relationship

$$\sum_k X^k = [1-X^n]/[1-X];\ 0 < X < 1 \qquad \text{(A.6)}$$

$k = 0,1,\ldots,n-1$

With these substitutions A.5 becomes

$$F_n = (1-a)^n \cdot F_o + [1 - (1-a)^n] \cdot C \qquad (A.7)$$

Put n = N(K). By definition, $F_o$ = F(K) and $F_{N(K)}$ = F(K+1); put W = (1-a). These substitutions and use of A.4 in A.7 lead to equation 1t.

Smoothing Constant W

Suppose again that successive updates of the initial overhaul factor for PRON K are made by use of the individual consumption quantities $C_n$ as explained above. Assume that the single exponential smoothing constant "a" to be used is chosen so that it corresponds to a moving average base period expressed in terms of reparable item completions. Let this base period be the yearly average maintenance program quantity P. Then, from the equivalence relationship given by equation 7, 1 - a = P-1/P+1; with N(K) denoting the completion quantity on PRON K,

$$W = (P-1/P+1)^{N(K)} \qquad (A.8)$$

The average maintenance program quantity P for a reparable item scheduled to be overhauled may take on any integer value with 1 as the lowest possible value. On any given program characterized by the value of P, the reparable item quantity, N, completed on one of the PRONs established for this program may also take on any integer value also with 1 as the lowest possible value. Small values of P are typical for low density equipment.

Consider some examples. Suppose that P = 1 and that the one reparable item is scheduled for overhaul under one PRON to be completed within the next 12 months. Suppose further that this particular item had experienced many PRONs in the past for which requirements for a given repair part had been forecasted via the overhaul factor approach. By A.8, W = 0 in

this case, so that the overhaul factor forecast determined from equation 16 for the upcoming PRON would be based solely on the last observation (Q/N) but would not reflect any other part of the overhaul consumption history. This waste of past experience appears undesirable.

Suppose now that P = 2. If 2 PRONs are established to complete this program, with N = 1 on each of the PRONs, then W = 1/3. If 1 PRON is established for this program, then N = 2 and W = 1/9. If consumption experience in the past had been relatively stable, either one of these two possible weights may be too low from the viewpoint of introducing undue perturbation in the forecast as was discussed in connection with adaptive exponential smoothing (paragraph 3.3).

To attenuate some of these undesirable aspects which are particularly drastic when P is small, we introduce the "average weight" denoted by AW and defined by

$$AW(P) = (1/P) \cdot \sum_{N} [P-1/P+1]^{N} \qquad (A.9)$$

$$N = 1,2,\ldots P.$$

The probability that N exceeds P in actuality will be assumed to be much smaller than the probabilities associated with N values less than or equal to P. Under this assumption the expected value of AW would not be significantly affected by limiting N to the range from 1 to P.

It can be shown (reference 25) that

$$\lim_{P \to \infty} AW(P) \approx 0.43 \qquad (A.10)$$

Limiting the accuracy to one decimal digit, define a "small" program quantity $P = P_o$ by

$$AW(P_o) = 0.4 \qquad (A.11)$$

Solving A.9 with this value yields $P_o$ = 12 (approximately). Substituting $P_o$ for P in A.8 yields W = 11/13 ; this, together with A.8 constitute equations (17) in paragraph 3.3.

From the definition of P (equation 14) it may be argued that N could be as high as 3 times the value of P. In this case, the limit as P approaches infinity is approximately 0.16 which corresponds to a P value of about 90; in the depot overhaul context this would less likely be considered a "small" program than would P = 12.

Other approaches to find suitable values for the smoothing constant for small programs could be taken. In this study, considerations were limited to those described above.

## REFERENCES


1 Kruse, W. Karl, "Comparison of Asset Return Forecasting Techniques," AMC Inventory Research Office, US Army Logistics Management Center, Fort Lee, Va., December 1974.

2 HQ AMC, Director of Maintenance Special Assistant for Systems Development, "Maintenance Overhaul Factor Reporting System (MOFARS)," Briefing presented at the AMC Maintenance Conference, 3-5 December 74, Lexington-Blue Grass Army Depot, Lexington, Ky.

3 AMC Regulation, "Depot Maintenance Program Scheduling, Workloading and Reporting System," AMCR 750-28.

4 USAMC Logistic Systems Support Agency, "Parts SPEEDEX Management."

5 AMC Pamphlet, "Maintenance Programs," AMCP-750-100, Vol 1, 1 May 71 (Draft).

6 AMC Pamphlet, "Overhaul Consumption Data," AMCP-750-100, Vol 2, March 1973 (Draft).

7 AMC Pamphlet, "Maintenance Parts Explosion," AMCP 750-100, Vol 3, June 1973 (Draft).

8 AMC Pamphlet, "Depot Maintenance Parts Requirements List," AMCP 750-100, Vol 4, March 1973 (Draft).

9 USAMC Logistic Systems Support Agency, "Instructions for Implementation of Depot Maintenance Parts Consumption Data Reporting," March 1971.

10 Defense Logistics Studies Information Exchange, "Forecasting," US Army Maintenance Management Center, Fort Lee, Va., March 1973.

11 Wright, L.F., "A Method for Predicting the Total Number of Parts Required to Rebuild a Given Lot of End Item," USAMC Intern Training Center, Red River Army Depot, Texarkana, Texas, May 1969.

12 Winters, P.R., "Forecasting Sales by Exponentially Weighted Moving Averages," Office of Naval Research, ONR Research Memorandum No. 62, March 1959.

13 Hayes, R.E., "A Comparison of Short-Term Forecasting Models," US Naval Postgraduate School (Thesis), Monterey, California, Sep 1971.

14 Astrachan, M., Sherbrooke, C.C., "An Empirical Test of Exponential Smoothing," Rand Corporation Memorandum, RM-3936-PR, March 1964.

15 Brown, R.G., "Smoothing Forecasting and Prediction," Prentice Hall, 1963.

16 Lewis, C.D., "Scientific Inventory Control," American Elsevier Publishing Company, Inc., New York, 1970.

17 Trigg, D.W., Leach, A.G., "Exponential Smoothing With An Adaptive Response Rate," Operational Research Quarterly, Vol 18, 1967.

18 McGlothlin, W.H., Radner, R., "The Use of Bayesian Techniques for Predicting Spare Parts Demand," Rand Memorandum, RM 25-36, March 1960.

19 __________, Bean, E.E., "Application of The Bayes Techniques to Spare Parts Demand Prediction," Rand Memorandum, RM 2701, January 1961.

20 __________, "Development of Bayesian Parameters for Spare Parts Demand Prediction," Rand Memorandum, RM 3699-PR, July 1963.

21 Markland, R.E., "A Comparative Study of Demand Forecasting Techniques for Military Helicopter Spare Parts," Naval Logistics Quarterly, Vol 17, No 1, March 1970.

22 Axtell, L.L., "Forecasting Electronic Repair Parts Consumption for AMC Electronics Depots," USAMC Intern Training Center, Red River Army Depot, Texarkana, Texas, March 1974.

23 Quinn, J.C., "Comparison of Several Methods for Forecasting Repair Part Requirements," USAMC Intern Training Center, Red River Army Depot, Texarkana, Texas, April 1974.

24 Kaplan, A.J., "Exponential Smoothing With Grouped Data," AMC Inventory Research Office, US Army Logistics Management Center, Ft. Lee, Va., October 1974.

25 Fatianow, P.R., "Project Work Items - Overhaul Factor Forecasting," Unpublished, AMCIRO Memorandum For Record, 19 June 1974.

26 US Army Maintenance Board (Now Maintenance Management Center) "Depot Maintenance Production Line Stopper Program," Study Report, May 1973.

27 R.F. Olds et al, "System Analysis Study of the TACOM Rebuild System," US Army Tank-Automotive Command, August 1973.

DISTRIBUTION

| COPIES | |
|---|---|
| 1 | Deputy Under Sec'y of the Army, ATTN: Office of Op Resch |
| | Headquarters, US Army Materiel Command |
| 1 | AMCPA |
| 1 | AMCPA-S |
| 1 | AMCMS |
| 1 | AMCDLS |
| 1 | AMCMA |
| 1 | AMCSU-K |
| 1 | AMCSU-M |
| 2 | Commander, US Army Logistics Center, Ft. Lee, Va. 23801 |
| 2 | Defense Logistics Studies Info Exchange, ATTN: AMXMC-D |
| 2 | Commander, USA Tank-Automotive Command, Warren, Mich. 48090 |
| 2 | Commander, USA Armament Command, Rock Island, Ill. 61201 |
| 2 | Commander, USA Electronics Command, Ft. Monmouth, N.J. 07703 |
| 2 | Commander, USA Missile Command, Redstone Arsenal, Ala. 35809 |
| 2 | Commander, USA Missile Command, ATTN: Mr. Ray Dotson, AMSMI-DA |
| 2 | Commander, USA Troop Support Command, 4300 Goodfellow Blvd., St. Louis, Mo. 63120 ATTN: AMSTS-G |
| 2 | Commander, USA Aviation Systems Command, P.O. Box 209, St. Louis, Mo. 63130 |
| 1 | Commander, USA Safeguard Command, Research Park, Huntsville, Ala. |
| 2 | Commander, Army Automated Logistics Mgt Systems Agcy, Box 14505, St. Louis, Mo. 63168 |
| 2 | Director, AMC Logistics Systems Support Agency, Letterkenny Army Depot, Chambersburg, Pa. 17201 |
| 2 | Director, AMC Maintenance Mgt Center, Lexington-Blue Grass Army Depot, Lexington, Ky. 40507 |
| 1 | Director, Army Management Engineering Training Agency, Rock Island Arsenal, Rock Island, Ill. 61202 |
| 1 | Commandant, US Army Logistics Management Center, Fort Lee, Va. 23801 |
| 1 | Defense Supply Agency, DSQUH-LSO, Cameron Sta., Alexandria, Va. |
| 4 | Deputy Chief of Staff (I&L), HQ USMC-LMP-2, Washington, DC 20380 |
| 10 | Defense Documentation Center, Cameron Sta., Alexandria, Va. |
| 1 | Commander, US Air Force Logistics Command, WPAFB, Dayton, Ohio, ATTN: AFLC/XODA 45433 |
| 1 | US Navy Fleet Materiel Support Office, Naval Supply Depot, Mechanicsburg, Pa. 17055 |
| 1 | Mr. James Prichard, Navy Supply Systems Cmd, Dept of US Navy, Wash., D.C. |
| 1 | George Washington University, Inst of Management Science & Engineering, 707 22nd St., N.W., Washington, D.C. |

| COPIES | |
|---|---|
| 1 | Naval Postgraduate School, ATTN: Dept of Opns Anal, Monterey, Calif. 93940 |
| 1 | Air Force Institute of Technology, ATTN: SLGQ, Head Quantitative Studies Dept., Dayton, Ohio 43433 |
| 2 | The Army Library, Room 1A518, Pentagon, Wash., D.C. 20310 |
| 1 | US Army Military Academy, West Point, N.Y. |
| 1 | Logistics Management Institute, 4701 Sangamore Road, Wash., D.C. 20016 |
| 1 | General Research Corp., ATTN: Mr. Lee Stoneback, McLean, Va. 22101 |
| 1 | University of Florida, ATTN: Dept of Industrial & Systems Engineering, Gainesville, Fla. |
| 1 | RAND Corp., ATTN: Dr. Murray Geisler, Santa Monica, Cal. 90406 |
| 1 | Office, Asst Sec'y of Defense (Inst & Logistics) ATTN: Mr. George Minter, Pentagon, Wash., D.C. 20310 |
| 1 | Commander, AVSCOM, ATTN: Systems Analysis Directorate, P.O. Box 209, St. Louis, Mo. 63166 |
| 1 | US Army Materiel Systems Analysis Agency, ATTN: AMXSY-CL, Aberdeen Proving Ground, Md. 21005 |
| 1 | Commander, US Army Logistics Center, ATTN: Studies Analysis Div., Concepts & Doctrine Directorate, Ft. Lee, Va. 23801 |
| 1 | Wallace M. Cohen, Asst Director Systems Analysis, FGMSD, General Accounting Ofc, Wash., D.C. 20548 |
| 1 | ALOG Magazine, ATTN: Tom Johnson, USALMC, Ft. Lee, Va., 23801 |
| 1 | Commander, Air Force Logistics Cmd, ATTN: AFLC/AQMLE, Wright Patterson AFB, Dayton, Ohio 45433 |
| 1 | Operations Research Center, 1115 Etcheverry Hall, University of California, Berkeley, Calif. 94720 |
| 1 | Commander, US Army-Tank-Automotive Command, ATTN: Mr. Joseph Neuse, AMSTA-S, Warren, Mich. 48090 |
| 1 | Major Keith Oppemmeer, HQ Dept of the Army, (DASG-HCL-P), Washington, D.C. 20310 |
| 1 | Dr. Jack Muckstadt, Dept of Industrial Engineering & Operations Research, Upson Hall, Cornell University, Ithaca, N.Y. 14890 |
| 1 | Prof Herbert P. Galliher, Dept of Industrial Engineering, University of Michigan, Ann Arbor, Mich. 48104 |
| 1 | Commander, USA Troop Support Command, ATTN: Mr. Homesley, AMSTS-F, 4300 Goodfellow Blvd., St. Louis, MO 63120 |
| 1 | Commander, US Army Electronics Command, ATTN: Mr. Lee, AMSEL-SA, Ft. Monmouth, NJ 07703 |
| 1 | Commander, US Army Armaments Command, ATTN: AMSAR, Rock Island, IL 61201 |
| 1 | Mr. Ellwood Hurford, Scientific Advisor, Army Logistics Center, Ft. Lee, VA 23801 |
| 1 | Commandant, USA Armor School, ATTN: MAJ Harold E. Burch, Leadership Dept, Ft. Knox, Ky. 40121 |
| 2 | Commander, Major Item Data Agency, Letterkenny Army Depot, Chambersburg, Pa. 17201 |